Integrating Saliency Ranking and Reinforcement Learning for Enhanced Object Detection

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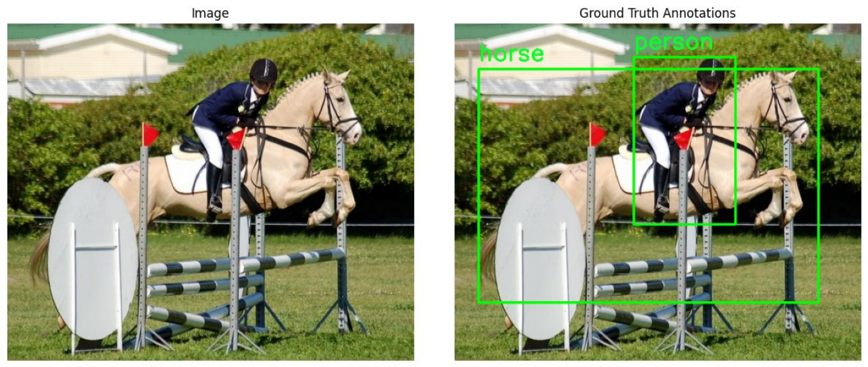
What is Object Detection?

Find objects in an image that belong to a predefined set of classes (e.g. person, motorbike, cat, etc.)

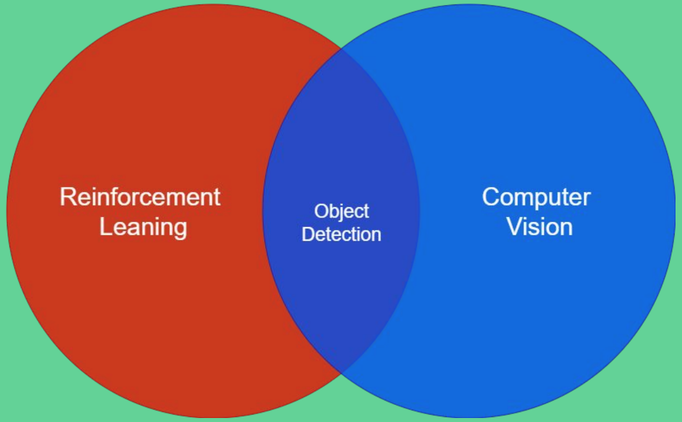


Images from Pascal VOC

Our Research Hypothesis:

“Can the combination of Reinforcement Learning with Saliency Ranking lead to Better and Enhanced Detection for Transparent and Sustainable solutions? “

Warning: Not your typical YOLO Object Detection application. . .



Combining two fields together

Human Perception

How can object detection systems emulate human-like proficiency?

Embarking on this Journey: Aims and Objectives

Objective 1 (O1) Develop an RL-based object detector framework.

Objective 2 (O2) Integrate saliency ranking to enhance object detection.

Objective 3 (O3) Create real-time visualisations for observing the RL environment.

Objective 4 (O4) Evaluate different feature learning networks and DQN variants for enhanced object detection.

Let’s Briefly Go Over the Literature:

A Brief Overview of Deep Learning Techniques for OD

Object Detection

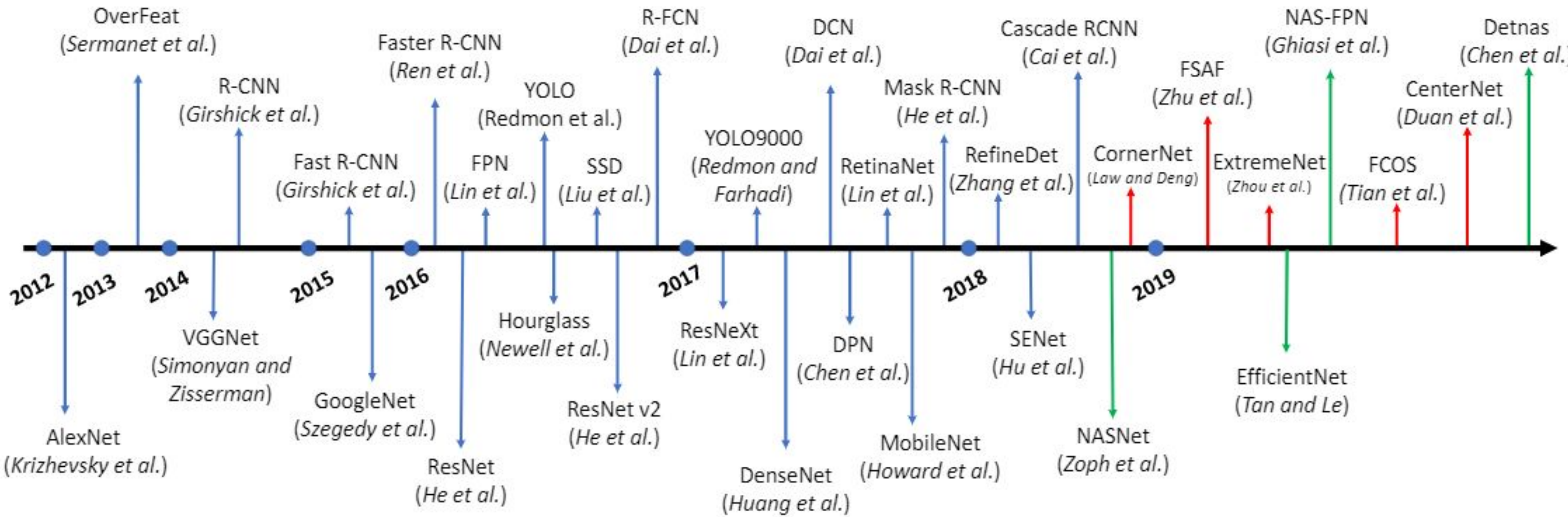


Image Classification

(Source: [1])

Reinforcement Learning Object Detectors

1. Active object localization with deep reinforcement learning **(2015)**
2. Hierarchical object detection with deep reinforcement learning **(2016)**
3. Reinforcement learning for visual object detection **(2016)**
4. Tree-structured reinforcement learning for sequential object localization **(2017)**
5. Deep reinforcement learning of region proposal networks for object detection **(2018)**
6. Object localization using deep reinforcement learning mohammad otoofi **(2018)**
7. Multitask learning for object localization with deep reinforcement learning **(2019)**
8. BAR - A reinforcement learning agent for bounding-box automated refinement **(2020)**
9. Efficient object detection in large images using deep reinforcement learning **(2020)**
10. Étude de la localisation active d'objets par apprentissage par renforcement profond **(2020)**
11. A reinforcement learning embedded object detection framework with region selection network **(2021)**
12. Object detection with deep reinforcement learning **(2022)**

Our Approach:

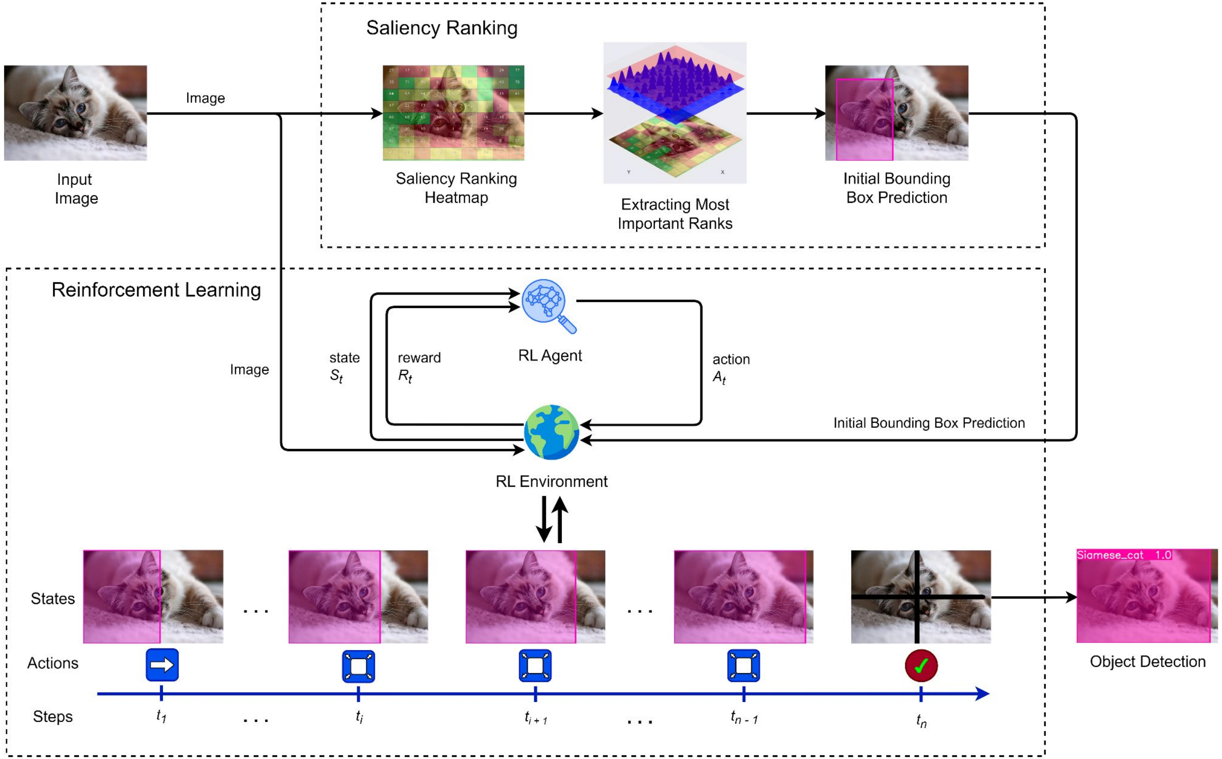
Smaller, Faster, and. . .

Explainable

SaRLVision

When compared to existing single object
RL- based detectors

Here's how we did it:



Not All Detectors Are Transparent

Isn't this essential? Given that the EU AI Act implies that AI should be explainable or interpretable.

SaRLVision

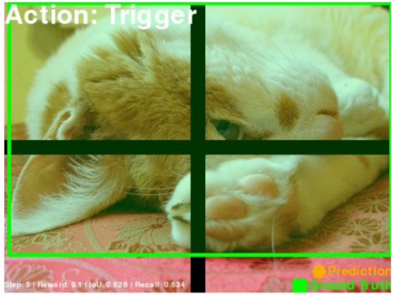
"Offers a self-explainable system with a fully observable action log."

Can YOLO do this?

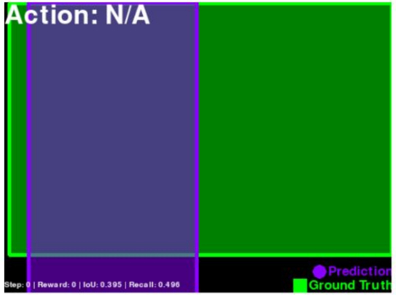
Self-Explainability - Render Modes

Training Mode (human)

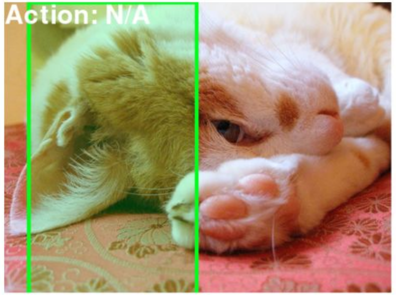
Training Mode (trigger_image)

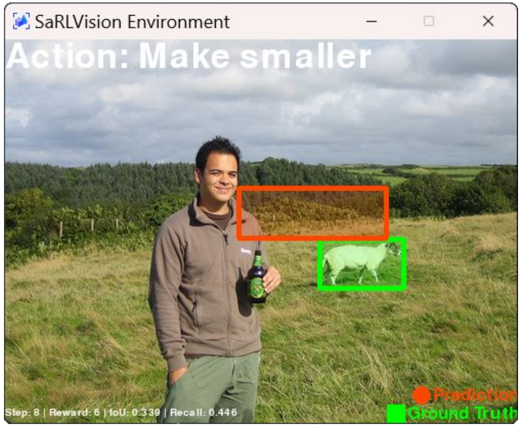


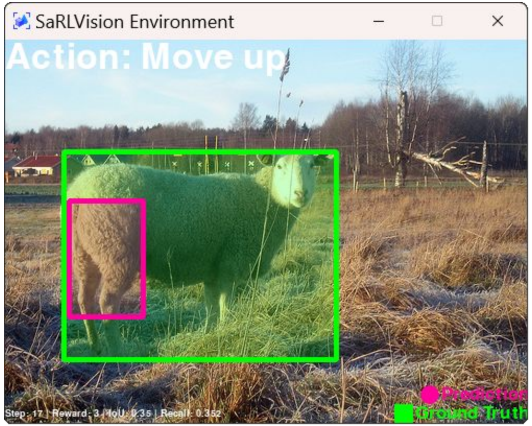
Training Mode (bbox)

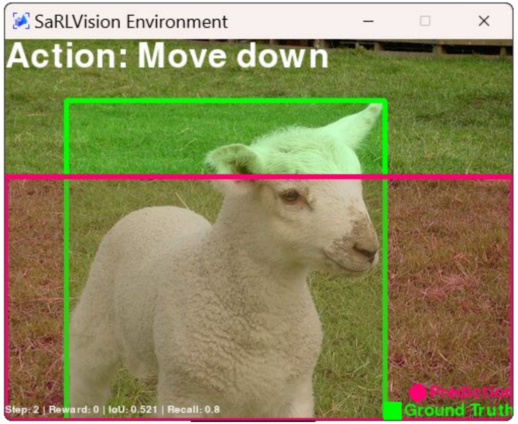


Testing Mode (human)



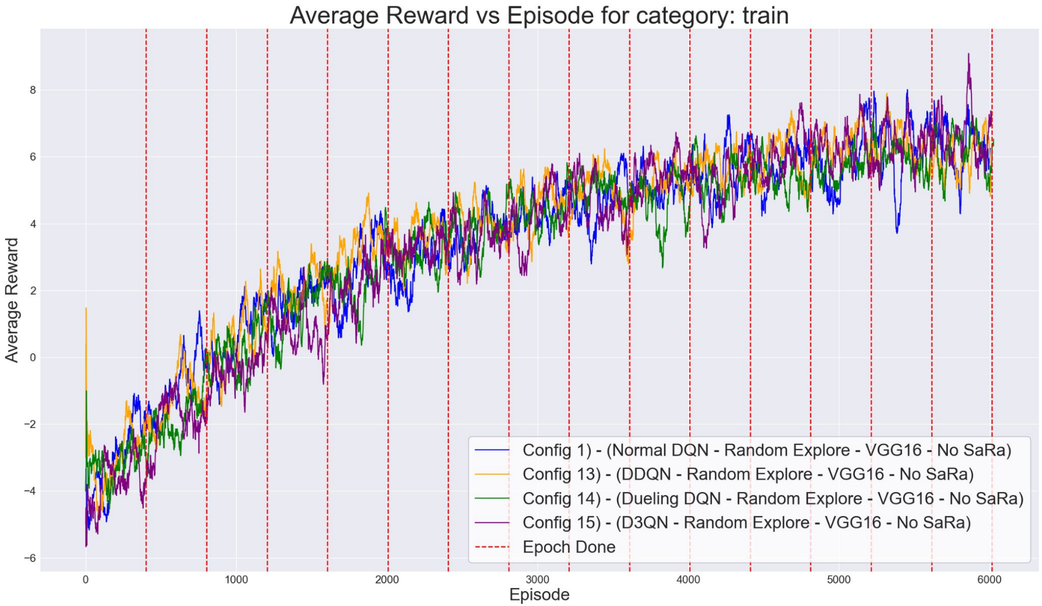






Self-Explainability - Fully Observable Action Log

Tracking the Reward Trajectory throughout Training:

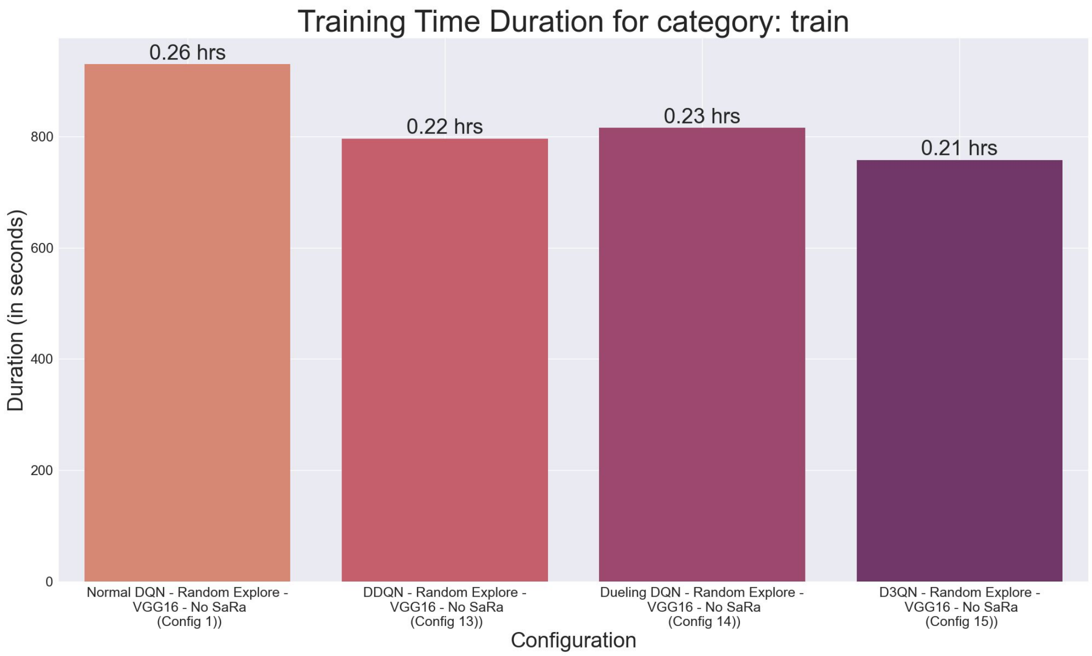


Average Reward vs Episode for category: train

Tracking the Training Time:

Comparison wise, in the literature for single object detection, it took approximately **3 hours** to train one category [2]. This was confirmed when testing locally.

Quite an improvement - **0.21 hours**!



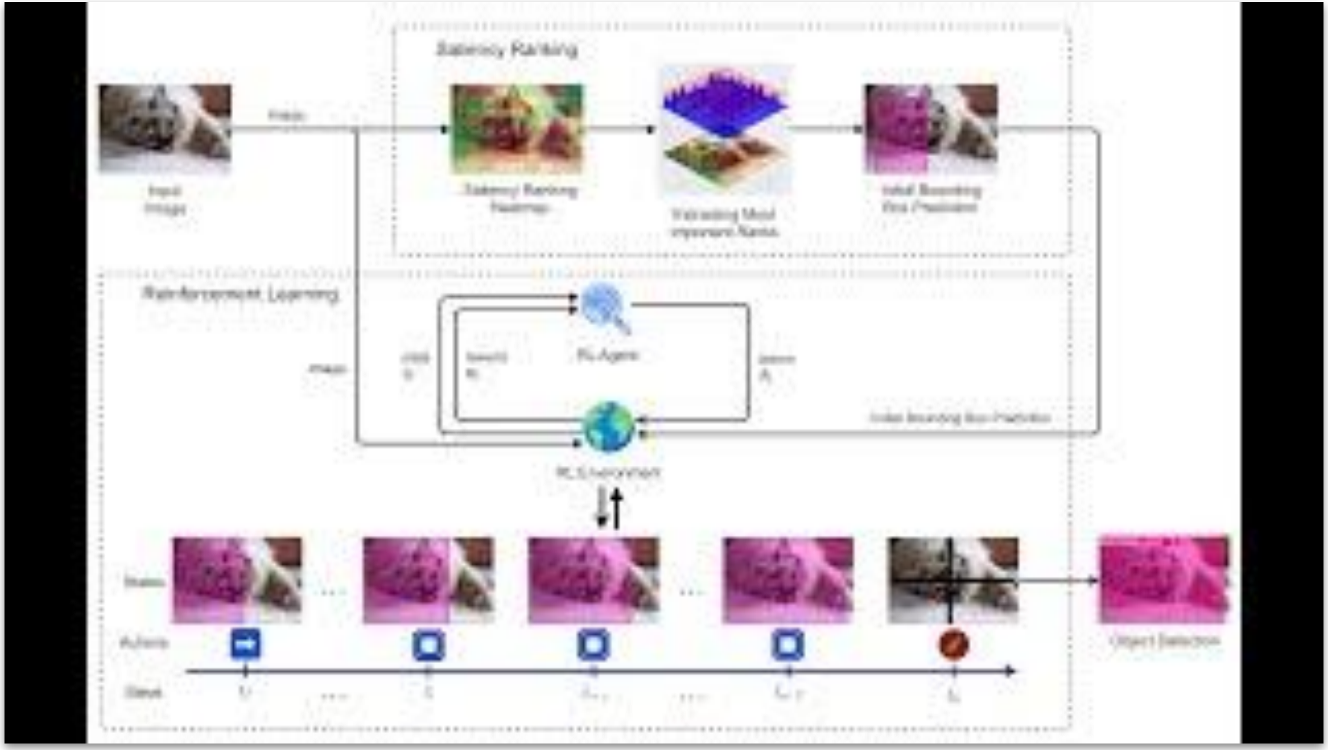
Training Time for category: train (Experiment 4)

How 2.5 Weeks of Round-the-Clock Evaluation Look Like:

Index	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
Caicedo et al (TR) [63]	57.9	56.7	38.4	33.0	17.5	51.1	52.7	53.0	17.8	39.1	47.1	52.2	58.0	57.0	45.2	19.3	42.2	35.5	54.8	49.0	43.9
Caicedo et al (AAR) [63]	55.5	61.9	38.4	36.5	21.4	56.5	58.8	55.9	21.4	40.4	46.3	54.2	56.9	55.9	45.7	21.1	47.1	41.5	54.7	51.4	46.1
S. R. Ramoul [78]	51.4	30.0	20.4	7.0	1.8	43.0	15.0	52.7	3.2	24.1	37.0	43.7	50.0	45.5	15.6	4.4	12.5	39.9	39.0	9.4	27.3
Config 1) (Ours)	76.4	25.7	64.3	18.3	4.1	**74.6**	**67.9**	73.1	4.1	64.3	34.1	29.8	**82.7**	73.9	38.8	6.6	68.9	21.3	52.9	55.7	46.9
Config 2) (Ours)	60.2	14.0	13.5	60.0	4.3	70.1	60.1	68.7	15.3	12.7	65.1	18.4	64.3	21.0	67.8	**65.2**	69.2	20.9	12.5	1.2	39.2
Config 3) (Ours)	70.8	30.3	**72.1**	17.7	19.9	49.3	63.9	66.9	6.2	21.6	33.4	**66.0**	70.1	72.6	22.4	7.2	44.4	21.5	72.1	14.1	42.1
Config 4) (Ours)	74.0	65.2	22.6	9.2	6.7	35.3	30.0	34.4	1.2	22.6	67.9	25.2	69.2	32.5	20.8	58.9	**70.0**	23.1	42.9	2.7	35.7
Config 5) (Ours)	65.5	17.8	67.8	11.3	2.2	39.1	64.5	64.8	**65.6**	26.5	66.9	62.0	74.8	32.0	22.5	5.0	16.4	21.6	71.9	3.8	40.1
Config 6) (Ours)	27.6	26.2	20.0	12.8	58.6	72.4	62.1	59.1	59.1	14.8	62.5	60.7	60.7	18.6	**68.8**	1.7	13.8	59.1	69.7	2.6	41.5
Config 7) (Ours)	74.3	18.8	21.3	17.7	1.9	25.7	66.4	24.3	4.3	64.8	71.9	30.1	30.6	62.3	22.1	1.8	12.5	25.3	73.7	3.9	32.7
Config 8) (Ours)	**76.8**	16.2	33.2	18.0	25.2	31.8	23.2	64.7	4.9	22.2	34.5	39.5	74.1	23.3	61.5	6.8	20.2	25.1	69.8	2.9	33.7
Config 9) (Ours)	56.2	23.6	45.6	26.5	3.5	68.6	67.0	33.7	4.3	17.5	68.2	45.1	76.2	45.2	20.4	4.8	66.3	63.9	**76.5**	15.4	41.4
Config 10) (Ours)	72.6	62.6	22.0	18.4	**65.1**	33.6	65.2	44.9	15.4	**65.7**	28.2	63.4	70.1	30.5	11.2	10.0	64.9	18.2	68.0	**64.3**	44.7
Config 11) (Ours)	74.4	27.6	35.6	61.5	14.7	34.2	64.2	43.9	4.7	62.8	**73.4**	24.8	81.1	71.8	16.2	5.3	22.5	65.4	76.3	2.9	43.2
Config 12) (Ours)	70.6	19.2	60.2	30.1	2.4	37.8	23.6	**75.2**	3.2	61.2	63.3	37.5	21.6	22.2	9.1	4.0	29.6	63.8	67.8	1.9	35.2
Config 13) (Ours)	64.0	26.5	20.9	20.7	7.4	40.8	48.7	71.5	4.2	36.3	25.7	**66.0**	80.5	38.1	25.1	15.0	63.8	65.2	73.8	4.4	39.9
Config 14) (Ours)	76.4	62.0	46.9	62.2	3.1	69.6	36.6	66.8	4.0	29.6	64.1	23.4	78.1	**75.3**	31.2	62.6	69.6	33.9	68.7	14.9	49.0
Config 15) (Ours)	76.0	**74.2**	67.1	**64.7**	4.7	72.7	64.5	68.7	3.6	33.7	23.4	34.0	77.2	71.5	64.9	3.2	23.1	**67.5**	73.6	59.3	**51.4**
Best Category APs (Ours)	76.8	74.2	72.1	64.7	65.1	74.6	67.9	75.2	65.6	65.7	73.4	66.0	82.7	75.3	68.8	65.2	70.0	67.5	76.5	64.3	70.6

Average Precision (AP) per Category and Mean Average Precision (mAP) in the Pascal VOC 2007 Test Set.

Need a Demo?



Conclusion

Conclusions:

1. An Object Detector built by Combining both Computer Vision & Reinforcement Learning
2. A Self-Explainable Approach
3. An Optimised Pipeline
4. Extensive Testing via (previously unseen) multiple DQN Agents such as Dueling DQN, and D3QN which generated the best Results
5. Better Accuracy, Speed, and Smaller Models

Future Work

Future Works:

1. Adoption of a Continuous Action Space
2. Training state-of-the-art Rainbow DQN
3. Re-imagining the (Object Detection) MDP problem
4. A tool to interpret between input features and action taken (xAI)

References

[1] Ram Sagar, "How The Deep Learning Approach For Object Detection Evolved Over The Years," Analytics India Magazine, August 26, 2019. [Online]. Available: https://analyticsindiamag.com/how-the-deep-learning-approach-for-object-detection-evolved-over-the-years/. [Accessed: March 23, 2024].

[2] S. R. Ramoul, Rapport bibliographique: Étude de la localisation active d’objets par apprentissage par renforcement profond, Sorbonne Université, Encadré par Pr. Isabelle Bloch, Nov. 2020. [Online]. Available: https://github.com/rayanramoul/Active-Object-Localization-Deep-Reinforcement-Learning. [Accessed: March 23, 2024].

Thank you!

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